Long-term Peak Load Forecasting Using LM-Feedforward Neural Network for Java-Madura-Bali Interconnection, Indonesia

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Abstract – *This paper presents the application of artificial neural network (ANN) based on multi-layered feedforward backpropagation for long-term peak load forecasting (LTPF). A four-layered network using Levenberg-Marquardt (LM) learning algorithm is proposed to forecast annual peak load of Java-Madura-Bali interconnection, Indonesia, for the period of 2009-2018 considering 11 regional factors encompass economic, electricity statistics, and weather thought to affect the load demand. The proposed network structure is first trained over the past 11 years (1995-2005) to forecast annual peak load of 2006-2008. Afterwards, the justified network structure is trained over the past 14 years (1995-2008) to forecast annual peak load of 2009-2018. Several simulations involve changes in historical actual peak load target and variation on projected regional economic growth are carried out to observe the network adaptability. Results are then compared with that achieved by the multiple regression model and projection made by utility. In this case, forecasting result exhibited by the proposed network is the closest to actual values of 2006-2009 among others taken the average error of 0.2%. Likewise, its forecasting differences for 2010-2018 are less than 7% compared to others. In term of network adaptability, outputs generated by the network are well adjusted to the projected inputs variation.*

Keywords – Artificial neural network, Java-Madura-Bali interconnection, LM algorithm, long-term peak load forecasting.

1. INTRODUCTION

Annual peak load forecasting is substantial to meet long-term electricity demand appropriately through system planning and expansion. In the long run, LTPF is a prominent precondition to establish the national electricity policy with respect to energy resources utilization and the selection of appropriate energy technologies based on the least cost, taken into account the environmental issues.

Two general methods have been applied on LTPF are artificial inteligent (AI) and econometric. Over the decades, ANN has been extensively used on this area and it has reported satisfactory performance better than that achieved by econometric method [1]-[4]. ANN offers flexibility in applying the customized model in order to increase its capability of pattern mapping as well as to meet certain requirement.

In the case of Java-Madura-Bali interconnection (hereafter "JaMaLi"), Indonesia, a LTPF has been done using Feedforward network with variable learning rate algorithm for 2007-2025, taken into account 10 actual historical data of 2001-2006 [5]. However, there is no verification in term of the network performance in the absence of comparison between the network forecasting result and the corresponding actual peak load.

In this paper, a four-layered LM-feedforward structure is proposed for the case of JaMaLi taken into account 11 actual historical and projection factors in economic, electricity statistics, and weather during the period of 1995-2018. Benefits of LM algorithm over variable learning rate and conjugate gradient method are reported in [6]. The overview of electricity sector in Indonesia, methodology, simulations and results, and conclusion are described further in the following sections.

2. OVERVIEW OF ELECTRICITY SECTOR IN INDONESIA

The total national installed capacity of electricity supply until mid 2008 was 29,885 MW, of which the state-owned enterprise (hereafter "PLN") contributed 24,924 MW or 83.39%, whereas private power generation companies contributed 4,044 MW or 13.53%, followed by captive power accounted for 916 MW or 3.08% [7]. In 2008, total installed capacity under the PLN system for JaMaLi was 18,538 MW, composed of 87.1% thermal power plants and 12.9% hydropower plants [8].

The total national electricity consumption was around 129,100 GWh, of which 128,810 GWh consumed through PLN system, where JaMaLi was accounted for 100,425 GWh. As per sector wise, industrial sector in JaMaLi was consumed the highest electricity accounted for 42,554 GWh, followed by residential sector with 35,929 GWh. However, the highest sectoral growth for 1995-2008 was attained by commercial sector as it has grown from 4,071.75 GWh to 16,947.63 GWh, or 316.2% [8]-[9].

The JaMaLi's peak load has reached 16,307 MW or 98.6% of the total available capacity in 2008, which was very critical to the system at that moment. According to the projection made by PLN, the electricity consumption in JaMaLi is expected to grow up for 9.5% on average annually starting from 2009 and will reach 250.9 TWh by 2018. Likewise, the JaMaLi peak load has been projected to reach 18.85 GW in 2009 and 43.63 GW by 2018, or equivalent to 9.49% per year [11].

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3. METHODOLOGY

3.1 Network data set

Actual historical data over the past 14 years (1995-2008) are applied as an input vector to the network considering input consistency as several electricity statistics data prior 1995 are based on government fiscal calendar. The input variables with respect to JaMaLi are: (1) Gross Regional Domestic Product (GRDP) with adjusted deflator, (2) population, (3) number of households, (4) total electricity energy consumption, (5) total installed power contracted, (6-9) electricity energy consumption in residential sector, commercial sector, industrial sector, and public sector, (10) electrification ratio, and (11) cooling degree days (CDD). JaMaLi's annual peak load during the same period are taken as the training output target.

In addition, the same 11 factors as it has been officially projected are assembled accordingly together with the JaMaLi's annual peak load projection made by PLN for 2009-2018 [9]. In term of weather factor, CDD is derived from the daily average temperature of the capital city Jakarta and its projection, accordingly.

3.2 Network Structure

A four-layered network structure comprises input layer, two hidden layers, and output layer is applied based on feedforward backpropagation method. Transfer function 'tansig' is applied for the 1st layer to generate output between -1 to 1. Meanwhile, 'logsig' is used for the hidden layers as the output generated by the those layers should be within positive value, and 'purelin' is applied to the output layer, subsequently.

Number of hidden neurons is determined based on Jadid and Fairbairn method [12]. Given the number of training data in the range of 121-253, the total number of hidden neurons is in the range of 8 to 16. Selected total number of hidden neurons is 14, of which 8 neurons and 6 neurons are placed in the 2nd and 3rd layer, respectively. Number of weights is determined from the number of connection made by all neurons between the two layers, similarly, between all neurons with input variables for the network input weights.

Number of bias is determined according to the number of neurons in the referred layer. Meanwhile, weights and biases are initialized to follow Nguyen-Widrow method [13] in which the weight and bias value in the 1st to 3rd layer is limited in the range of -1 to 1, whereas for the 4th layer is limited in the range of -0.5 to 0.5, so that each neuron is distributed approximately evenly across the layer's space.

3.3 Training Algorithm

Backpropagation learning algorithm originally consists of 2 stages through the different layers of the network: forward pass and backward pass. In this paper, the forward pass is initially applied then it is followed by the LM algorithm to enhance the backward pass. The LM algorithm involves Jacobian matrix computation, of which calculated using the standard backpropagation algorithm with modification at the final layer [6].

The LM method is an approximation to the Newton method. Consider an error function $V(x)$ to be minimized with respect to the input vector x, the Newton method can be expressed as:

$$\Delta x = -[\nabla^2 V(x)]^{-1} \nabla V(x) \tag{1}$$

$$\nabla V(x) = J^T(x) e(x) \tag{2}$$

$$V(x) = \sum_{i=1}^{N} e_i^2(x) \tag{3}$$

where $\nabla^2 V(x)$ is the Hessian matrix; $\nabla V(x)$ is the gradient; and $V(x)$ is an error measurement function.

LM modification to the Gauss-Newton method is given by:

$$\Delta x = [J^T(x) J(x) + \mu I]^{-1} J^T(x) e(x) \tag{4}$$

where J is the Jacobian matrix in which contains first derivatives of the network errors with respect to the weights and bias; and e is a vector of network errors with respect to the input vector x.

The network training algorithm in this study proceeds as follows:

1. Apply preprocessing scheme to scale the input and target vector is conducted so that they always fall within a range of -1 to 1.
2. Present all treated inputs and corresponding target output from step 1 to the network and initialize weights and bias using Nguyen-Widrow method. Compute the corresponding network outputs and errors using forward pass of backpropagation, compute $V(x)$ over all inputs.
3. Compute the Jacobian matrix.
4. Solve Eq.4 to obtain Δx.
5. Recompute $V(x)$ using $x + \Delta x$. If the new $V(x)$ is smaller than that computed in step 2, then reduce μ by some factor γ, calculate $x + \Delta x$, go to step 2. If $V(x)$ is not reduced, increase μ by γ, go to step 4.
6. The algorithm is completed when error $V(x)$ is equal or lower than the predetermined error goal.

3.4 Network testing

In this paper, 5 simulations are presented to test the proposed network structure for which the network response in term of adaptation to different input and output target during training and forecasting period can be observed from each simulation result. The network input, training output target, objective, and result exhibited by each simulation is further described in the section 4.1.

3.5 Multiple Regression Model

The Double-log multiple regression model is applied as the comparison to the proposed ANN structure. The model comprises one dependent variable of peak load and 11 independent or explanatory variables, from the same 11 factors as mentioned in the section 3.1, are applied as explanatory variables for the model. The mathematical equation of the model is given as:

$$\ln Y_t = c + \beta 1 \ln X1_t + \beta 2 \ln X2_t + \ldots + \beta 11 \ln X11_t \qquad (5)$$

where $\ln Y_t$ is dependent variable for peak load as linear function of logs of regressor in period t; $X1_t$, $X2_t$, ..., $X11_t$ is the explanatory variable of the 1st to 11th factor in period t; $\beta 1$, $\beta 2$, ..., $\beta 11$ is coefficient of explanatory variable of 1st to 11th parameter, and t is year.

The forecasted peak load is calculated towards all explanatory variables with respect to 3 economic growth scenarios, which is described further in the section 4.2 and 4.3, subsequently.

4. SIMULATION AND RESULT

Numerical forecasting result and error comparison in term of Mean Absolute Percentage Error (MAPE) obtained from all network simulations and the multiple regression model are presented altogether with the actual peak load and with that made by PLN in Table 2 (Appendix).

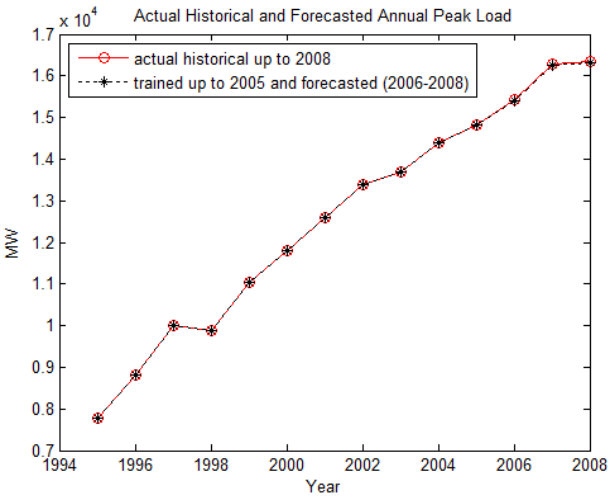

Fig. 1. Training and forecasting result of simulation-1.

4.1 LM-feedforward Network Structure

Simulations using the proposed network structure as described in the section 3.2 as well as using other structures with different number of neurons had been attempted. However, other network structure exhibited larger errors as the network output of 2006-2009 compared with its corresponding actual peak load.

All simulations applying the proposed network structure are described further in the following sections. Accordingly, comparison between network training and forecasting result either with actual peak load or with that made by PLN is shown graphically in each figure following to each simulation explanation.

Simulation-1

The actual historical data of 1995-2005 and actual peak load for the respective year is applied as the network input and training output target. Afterwards, network is simulated using data projection of 2006-2008 to obtain the corresponding peak load.

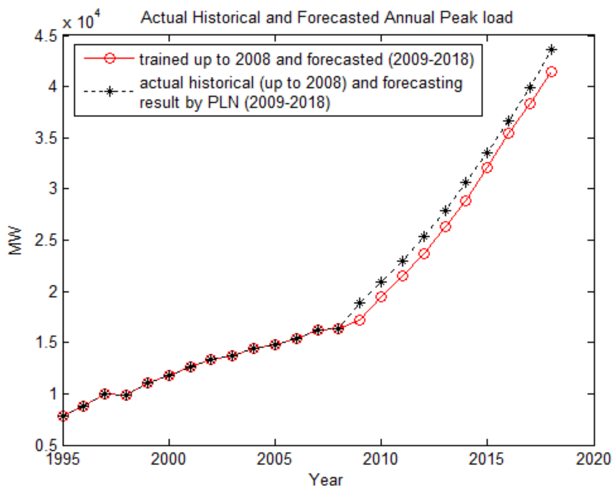

Fig. 2. Training and forecasting result of simulation-2.

Simulation-2

In this simulation, the same network structure as used in the simulation-1 is applied. Network input and training output target are actual historical data and actual peak load of 1995-2008, respectively. LTPF of 2009-2018 is obtained using the data projection of 2009-2018 as the network simulation input, including officially projected GRDP data during the forecasting period of 2009-2018.

Simulation-3

Network input is the same with that applied in simulation-2, which are actual historical data of 1995-2008. Meanwhile, slightly different target output is applied as the training output target are actual peak load of 1995-2005 and followed with the forecasted peak load of 2006-2008 obtained from simulation-1. LTPF of 2009-2018 is obtained using the same data projection as applied in simulation-2.

Simulation-4

Network input and training target output are are actual historical data of 1995-2008 and corresponding peak load as the training output target, respectively. LTPF of 2009-2018 with 5% additional to the officially projected GRDP is obtained considering higher GRDP growth.

Simulation-5

Network data set is the same with that applied in simulation-4. LTPF of 2009-2018 with 5% reduction to the officially projected GRDP during 2009-2018 is obtained from this simulation.

4.2 Multiple Regression Model

Comparison between actual historical peak load with that obtained by the Log-linear regression is given in Table 1.

Initially, all coefficients of explanatory variable of the regression equation is computed taken into account historical period of 1995-2008 to obtain regression fitted peak load as shown in Table 1. Afterwards, the regression equation is applied to calculate annual forecasted peak load with respect to all data projection in the period of 2009-2018. The results, of which given in Table 2 (see Appendix), involved 3 economic growth scenario: (1) officialy projected economic growth, (2) higher economic growth, and (3) lower economic growth.

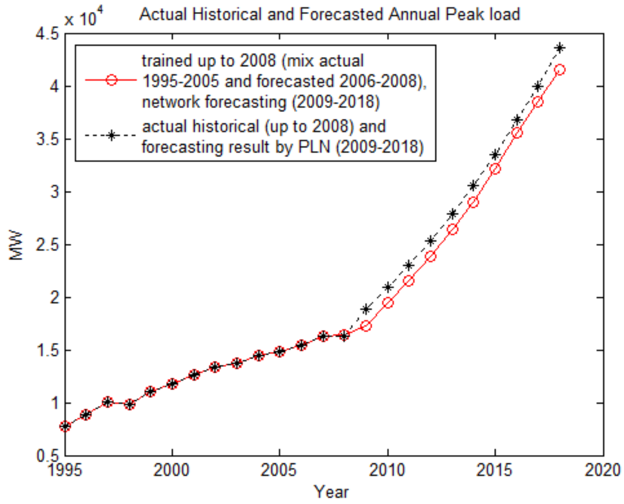

Fig. 3. Training and forecasting result of simulation-3.

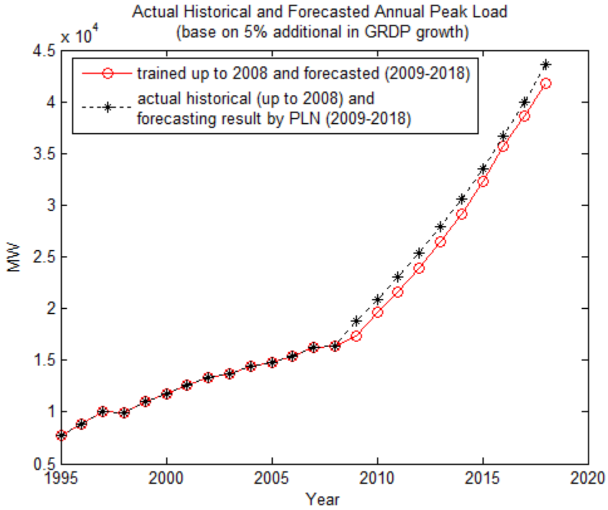

Fig. 4. Training and forecasting result of simulation-4.

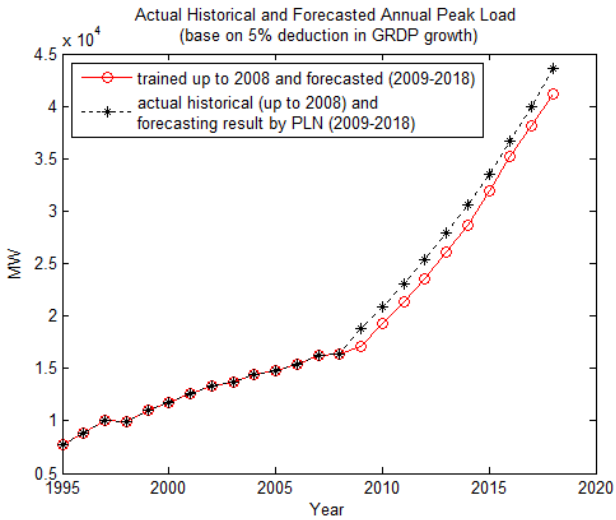

Fig. 5. Training and forecasting result of simulation-5.

Table 1. Actual and Double-log regression peak load

Year	Actual peak load	Regression peak load
1995	7,773	7,789
1996	8,823	8,765
1997	10,017	10,074
1998	9,877	9,973
1999	11,039	10,914
2000	11,801	11,765
2001	12,582	12,708
2002	13,379	13,502
2003	13,687	13,334
2004	14,403	14,532
2005	14,827	14,806
2006	15,402	15,451
2007	16,259	16,234
2008	16,309	16,423

4.3 Result comparison

Comparison in term of MAPE of the proposed network structure can be practically considered to be zero as exhibited in the training output during 1995-2008 whereas for Log-linear regression model is accounted for 0.75%. As presented in Table 2 (see Appendix), the network MAPE for simulation-1 (2006-2008) is 0.22%, of which far less than that projected by PLN, accounted for 3.16%. Likewise, the yearly errors exhibited by the network are tended to be steady whereas the PLN's errors are excalated.

In 2009, forecasting peak load of 17,269 MW, 18,788 MW, and 18,854 MW are exhibited by the proposed network (simulation-3), regression model, and PLN, respectively. The least forecasting error is obtained by the proposed network for 0.34%, followed by regression model and PLN, for 9.16% and 9.55%, respectively. In addition, results difference between the proposed network under simulation-2 and simulation-3 with that available from PLN are less than 7%, which is said to be acceptable for utility's LTPF [14]. In term of network adaptability (see Table 2, Appendix), the simulation result is affected by applying changes in training output target as overall result exhibited by simulation-3 are slightly higher compared with that obtained by simulation-2.

Effect of GRDP variation on LTPF, economic growth can be observed accordingly from network simulation as well as multiple regression model. Overall forecasting peak load given by simulation-4 are higher in magnitude during 2009-2018, of which in the range of 157 MW to 366 MW, compared with that given by simulation-2. On the other hand, results obtained from simulation-5 are lower, in the range of 118 MW to 203 MW over the same forecasting period, compared with that achieved by simulation-2. Hence, the differences between network's output and PLN's projection are becoming larger than that in simulation-2. Meanwhile, the effect of GRDP variation in the Double-log regression model is not as significant as in the proposed network as the annual peak load forecasting differences between both higher and lower case to the base case are in the range of 7 MW to 16 MW.

5. CONCLUSION

ANN is characterized by (1) its architecture, (2) its training or learning algorithm, and (3) its activation function, for which the network performance would be mostly depend on, beside on the input variable selection and the network structure. Development of network structure involves decision making on type of network architecture and network size, in term of number of layers and neurons to be used. One reason for selecting a training algorithm is to speed up convergence and to avoid network from being trapped in the local minima.

In this paper, several simulations using the proposed LM-feedforward network have been conducted for LTPF problem of JaMaLi, Indonesia. The results exhibited by the network are much better in term of forecasting error than that given by the regression model and projection made by PLN. Regarding to the network adaptability, applying different input and training output target has resulted variation of the network output in respective manner. Thus, the proposed network struture can be considered as promising alternative method for JaMaLi's LTPF.

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APPENDIX

Table 2. Forecasting result and error comparison in percentage (MAPE)

Year	Actual* Peak load	Network simulation					Multiple regression model			PLN#
		1	2	3	4	5	1	2	3	
		(% error or differences with PLN)								
2006	15,402	15,434 (0.21)								15,400 (0.01)
2007	16,259	16,297 (0.23)								16,478 (1.35)
2008	16,309	16,347 (0.23)								17,631 (8.11)
2009	17,211		17,225 (0.08)	17,269 (0.34)	17,382 (0.99)	17,107 (0.60)	18,788 (9.16)	18,796	18,781	18,854 (9.55)
2010			19,463 (6.88)	19,508 (6.66)	19,629 (6.08)	19,338 (7.47)	20,870	20,878	20,863	20,900
2011			21,472 (6.70)	21,527 (6.45)	21,646 (5.94)	21,328 (7.31)	23,212	23,221	23,203	23,012
2012			23,731 (6.36)	23,791 (6.12)	23,922 (5.61)	23,585 (6.94)	25,723	25,733	25,713	25,343
2013			26,271 (5.86)	26,342 (5.60)	26,486 (5.09)	26,127 (6.37)	28,585	28,596	28,574	27,906
2014			28,867 (5.65)	28,946 (5.40)	29,092 (4.92)	28,706 (6.18)	31,656	31,668	31,645	30,597
2015			32,062 (4.39)	32,159 (4.10)	32,318 (3.63)	31,897 (4.88)	34,956	34,969	34,944	33,535
2016			35,445 (3.44)	35,561 (3.12)	35,704 (2.74)	35,268 (3.92)	38,111	38,124	38,097	36,708
2017			38,346 (4.01)	38,475 (3.69)	38,646 (3.26)	38,160 (4.49)	41,575	41,589	41,560	39,949
2018			41,407 (5.09)	41,541 (4.79)	41,773 (4.25)	41,204 (5.56)	45,242	45,258	45,226	43,629

#) PLN forecasting for 2006-2008 is based on RUPTL 2006-2015 [10], 2009-2018 is based on RUPTL 2009-2018 [11].
*) Actual peak load for 2009 is based on JaMaLi Transmission and Load Dispatching Centre (http://*www.pln-jawa-bali.co.id)*